

Urban socioeconomic patterns revealed through morphology of travel routes

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Abstract

The city is a complex system that evolves through its inherent social and economic interactions. Mediating the movements of people and resources, urban street networks offer a spatial footprint of these activities; consequently their structural characteristics have been of great interest in the literature. Missing from the analysis is the specific interplay between street structure and its functional usage, i.e the movement patterns of people and resources. To address this limitation, we study the shape of 472,040 spatiotemporally optimized travel routes in the 92 most populated cities in the world. The routes are sampled in a geographically unbiased way such that their properties can be mapped on to each city, with their summary statistics being representative of meso-scale connectivity patterns. To characterize each city's morphology, we propose a comprehensive metric, *inness*, that examines the geometric shapes of the routes relative to the city center, presumably a hub of socioeconomic activity. The collective morphology of routes exhibit a directional bias that appears to be influenced by the attractive (or repulsive) *forces* resulting from congestion, accessibility and travel demand, which of course, relate to various socioeconomic factors. An analysis of the morphological patterns of individual cities reveals structural and socioeconomic commonalities among cities with similar inness patterns, in particular that they cluster into groups that are correlated with their size and putative stage of urban development. Our results lend weight to the insight that levels of urban socioeconomic development are intrinsically tied to increasing physical connectivity and diversity of road hierarchies.

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Introduction

The city is the ultimate archetype of a complex system, existing, and indeed evolving due to the myriad socioeconomic activities of its inhabitants [1–3]. These activities are mediated by the accessibility of urban spaces depending on the city topography and its infrastructural networks [4], a key component of which are the roads. Indeed, different street structures result in varying levels of efficiency, accessibility, and usage of the transportation infrastructure [5–11]. Structural characteristics, therefore, have been of great interest in the literature [12–15] and many variants of structural quantities have been proposed and measured in urban contexts, including the degrees of street junctions [16], lengths of road segments [15], cell areas or shapes delineated by streets [13], anisotropies [14], and network centrality [17, 18]. Collectively, these structural properties have uncovered unique characteristics of individual cities as well as demonstrated surprising statistical commonalities manifested as scale invariant patterns across different urban contexts [19–21].

While these studies have shed light on various facets of the statistical structure of these street networks, there is limited understanding on the interplay between the road structure and its influence on the movement of people and the corresponding flow of socioeconomic activity; that is, the connection between urban dynamics and its associated infrastructure [22]. One way to tease out this connection would be to examine the *sampling of routes*, that is an examination of how inhabitants of a city actually utilize the street infrastructure. A number of studies have been conducted research on the empirical factors behind the choice of routes [23–26], yet little effort has been made to attend to their geometric properties [23], that is their *morphology*.

Indeed, the morphology of a route is shaped by the embedded spatial pattern of a city (land use and street topology) in association with dynamical factors such as congestion, accessibility and travel demand which relate to various attendant socioeconomic factors. Analyzing the morphology of routes, therefore, allows us to uncover the complex interactions that are hidden within the coarse-grained spatial pattern of a city. Furthermore, the morphology also encodes the collective property of routes, including their long-range *functional* effects. For example, a single street, depending on its connectivity and location, can have influence that spans the dynamics across the whole city (Broadway or Fifth avenue in NYC for instance).

In particular, traffic patterns and the shape of routes have been shown to be determined, among other factors, by mainly two competing forces [24]. On the one hand, one finds an increased tendency of agglomeration of businesses, entertainments and residential concerns near the urban center, correspondingly leading to a higher density of streets [27, 28] and thus attracting traffic and flows *towards* the interior of the city (positive urban externality). Conversely, this increasing density leads to congestion and increase in travel times (negative urban externality) thus necessitating the need for arterial roads or bypasses along the urban periphery to disperse the congestion at the core. This has the effect of acting as an opposing force diverting the flow of traffic *away* from the interior of the city.

We investigate these two competing effects through a detailed empirical study of the *shape* of 472,040 travel routes between origin-destination points in the 92 most populated cities in the globe. Each route consists of a series of connected roads, accompanied information on their geographical location, length, and speed limit retrieved from the OpenStreetMap database [29]. We split our analysis between the shortest routes (necessarily constrained by design limitations and city topography) and the fastest routes (representing the effects of traffic and dynamic route sampling), with the former representing aspects of the city morphology, while the latter in some sense representing the dynamics mediated by the morphology. Specifically, the shortest routes are a function of the *bare* road geometric structure, while the fastest routes represent the *effective* geometric structure—a function of the heterogeneous distribution of traffic velocity resulting from varying transportation efficiency and congestion patterns [30–33].

To uncover the functional morphology of these two categories of routes, we define a novel topological metric, which we term *inness*—a function of both the direction and spatial length of routes—that captures the tendency of travel routes to gravitate towards or away from the city center. This metric serves as a proxy for the geographical distribution of *hidden* attractive forces that may be implicit in the sampling of streets (as reflected in directional bias) and that otherwise cannot be captured by existing measures. Our analysis represents a step towards the very important challenge of determining the spatial distribution of urban land-use and street topology to balance the inherent negative and positive urban externalities that result from rapid urbanization [24].

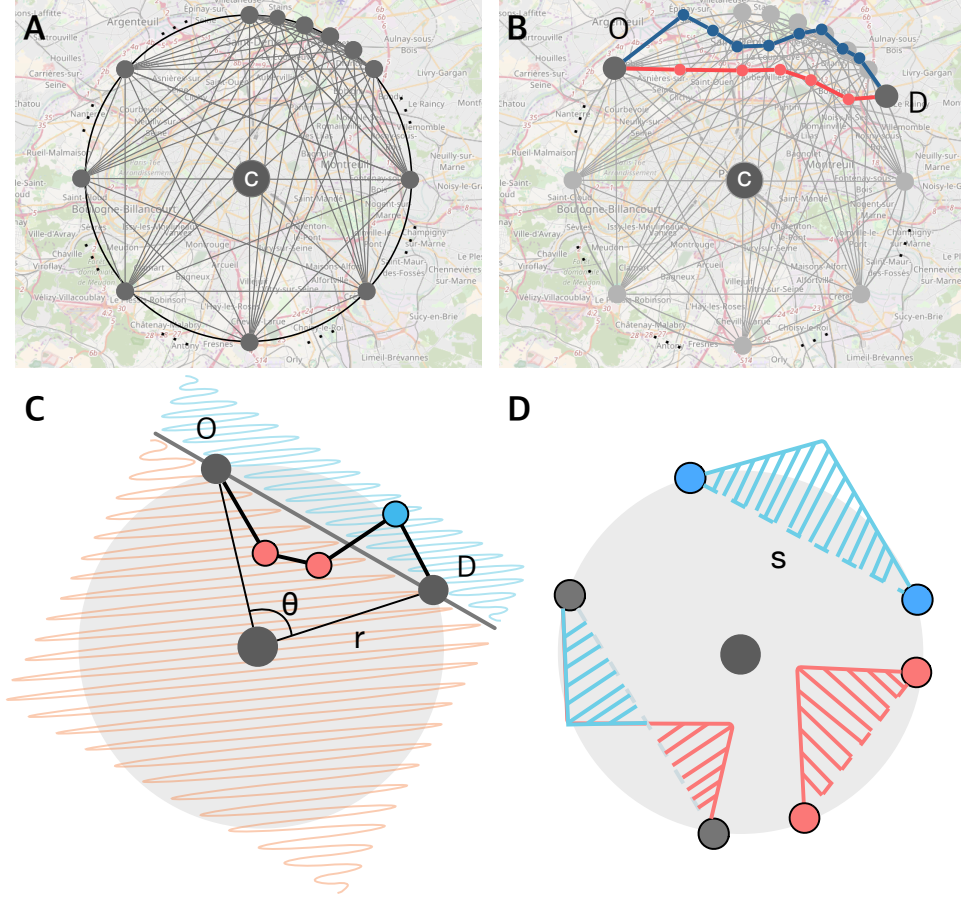


FIG. 1. **Data sampling and definition of Inness I** **A** 36 origin-destination (OD) pairs (spaced out at intervals of 10°) are assigned along the circumference of circles at a distance of 2km, 5km, 10km, 15km, 20km and 30km from the city center **C**. **B** For each OD pair, we query the Open Source Map API and collect the shortest routes (red) and the fastest routes (blue) (shown here for a representative OD pair in Paris). **C** A typical OD pair with the straight line connecting them representing the geodesic distance s ; r is the radial distance from the center and θ is the angular separation relative to the center. We define the Inness (I) to be the difference between the *inner* travel area (polygon delineated by red inner point and straight line) and the *outer* travel area (polygon delineated by blue outer point and straight line). **D** Three possible route configurations between multiple OD pairs. One with an exclusively outer travel area (blue), one with an exclusively inner travel area (red) and one where there is some combination of both.

Results

Sampling routing pairs For each of our 92 cities, a city center is defined by referencing the coordinates from `latlong.net` [34] and the travel routes are sampled according to a choice of origin-destination pairs (OD) relative to the center and measured in spherical coordinates (distance from center r , and angular separation relative to center θ). To avoid any sample bias, and to systematically investigate dependence of route morphology on distance from the urban center, we only consider OD pairs at a fixed radius r . Furthermore at each r we section the circumference of the circle at intervals of 10° for a total of 36 points (with the minimal angular separation chosen to avoid effects of noise). We then vary the radius over the range 2km, 5km, 10km, 20km and finally 30km (roughly corresponding to a city boundary) and enumerate over all OD pairs by connecting the 36 points at a given radius r for a total of $5 \times \binom{36}{2} = 3150$ total routes. Finally, we query the OpenStreetMap API for two different kinds of *actual routes* between all these pairs: the *shortest*, based on lengths of road segments, and the *fastest* that accounts for both the length as well as the travel time based on speed-limits. A visual representation of our methodology in segmenting the city is shown in Fig. 1A and typical examples of the shortest and fastest route for a given city is shown in Fig. 1B. (For full details of our data sampling and measurement methodology see SI Sec. S1 and Figs. S1–S3.)

Definition of Inness *I* Fig. 2 illustrates schematics of the *forces* hidden in the city’s morphological patterns, shaping, and shaped by infrastructure and socioeconomic layouts. For the case of a square grid, as shown in Fig. 2A, shortest routes between any two points at a distance r either correspond trivially to the the line connecting them directly, or are degenerate paths that traverse the grid in either direction. Taking the average of the multiple paths cancels any directional bias relative to the center of the grid. Yet, a small perturbation of this regularity can change this neutral feature dramatically, as shown in Fig. 2B, where we shift the four outermost points inwards as to place them on the second ring from the center. Points lying on this ring have shortest routes that lie along the periphery, thus introducing a dispersive force away from the center (marked as blue arrows). In Fig. 2C, we further perturb the topology by adding four lines from the outer ring to the inner ring (marked in green) thus increasing connectivity towards the center. Shortest paths between pairs on the outer ring traverse through the inner ring and are curved towards the city center, resulting

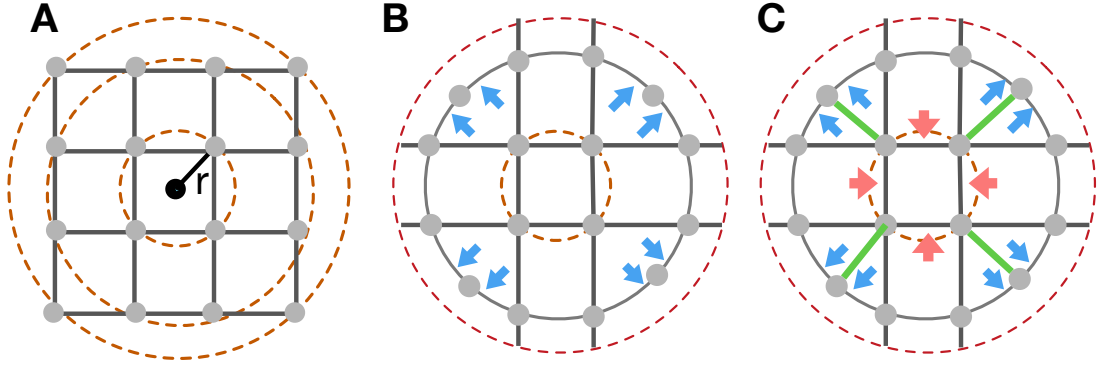


FIG. 2. **Biasing forces found in urban morphology** Three schematic urban street arrangements share similar topological structure, but different geometric layouts resulting in varying dynamics. **A** A grid structure where shortest paths between points at the same radius shows no directional bias. **B** Repulsive forces relative to the origin (marked in blue) emerge as we break the grid symmetry by relocating the four outer points on the inner equidistant ring-line. Paths lying on this ring now have shortest paths that traverse the periphery and avoid the center. **C** Further perturbing the topology by increasing connectivity to the center (marked as four green lines) now leads to shortest paths that go through the center as if an attractive force is present (marked in red).

in an attractive force (represented as red arrows).

Next, we define a metric, called the *Inness* I , that can capture the effective forces underlying observed routes. Fig. 1C illustrates how a typical route between any OD pair can be divided up into segments that are directionally biased towards, or away from the city center as measured relative to the geodesic distance s between the pair. Points lying below the geodesic (and therefore towards the center) are considered inner points, while those lying above, outer points. For example in the schematic shown in Fig. 1C the points located in the pink shaded area are the inner points, and those on the opposite side (shaded blue) are outer points. We define an *inner travel area* delineated by the polygon of inner points and the geodesic line, to which we assign a positive sign. Conversely, an *outer travel area* is defined by the geodesic line and the collection of outer points, whose sign is negative. Having adopted this convention, I is the difference between the inner area and outer travel

areas,

$$I = A_{\text{in}} - A_{\text{out}}. \quad (1)$$

More succinctly, I can be calculated by summing over the areas of the number of polygons in the route by using the shoelace formula thus,

$$I = \frac{1}{2} \sum_{i=1}^m \text{sgn}(i) \left| \sum_{j=1}^n \det \begin{pmatrix} x_{i,j} & x_{i,j+1} \\ y_{i,j} & y_{i,j+1} \end{pmatrix} \right|. \quad (2)$$

Here n is the number of vertices of the polygon, m is the total number of polygons in the route, $(x_{i,j}, y_{i,j})$ corresponds to the coordinate of j 'th vertex of polygon i , and $\text{sgn}(i)$ accounts for our adopted convention for inner and outer points. As an illustrative example of the cases we expect to measure from our data, in Fig 1D we show three possible idealizations of a route; one with only outer travel area (blue), one with only inner travel area (red), and one with a mixture of both outer and inner travel areas (combination of blue and red).

Average Inness for shortest and fastest routes We begin our analysis by an examination of the qualitative trends of I . In Fig. 3A, we plot the average inness $\langle I \rangle$ (averaged over the 92 cities in our dataset) for both the shortest (green curves) and the fastest routes (purple curve) as a function of the angular separation θ , for multiple radii r . In the vicinity of the city center (2-5km), we see a neutral trend for the shortest routes ($\langle I \rangle \approx 0$) although fluctuations increase with angular separation ($80^\circ \leq \theta \leq 160^\circ$). The fluctuations anticipate a clear *inward bias* that emerges at a distance of $r \geq 10$ km, visible as a pronounced positive peak in $\langle I \rangle$ that grows progressively sharp with increasing r . The qualitative trend of $\langle I \rangle$ is indicative of the presence of a core-periphery street network structure present in varying degrees across all cities [35]. For fixed r , the geodesic distance s between any OD pair is a monotonically increasing function in θ . The longer the distance, the more likely it is for the route to drift towards the center—due to greater connectivity in the center compared to the periphery—and therefore the observed inward bias. Near an angular separation of 180° , the geodesic passes through the city center, and I is necessarily zero by construction; thus $I \rightarrow 0$ for $\theta \geq 160$. Similarly, the increase in inward bias of routes with r is reflective of a progressively lower density of streets in the periphery.

For the fastest routes $\langle I \rangle \approx 0$ up to 5km. At a distance of 10km, one begins to see an inward bias, but markedly less pronounced than seen for shortest routes, although the qualitative trend of increasing inward bias with r is maintained. The lower inward bias

of faster routes can be explained by the fact that they usually correspond to bypasses or highways that are typically located in the periphery of cities. Yet, two features stand out: first, the angular range of the observed inward bias is *lower* than that seen for shortest paths ($45^\circ \leq \theta \leq 120^\circ$). Second, the fluctuations are significantly larger, indicating a heterogeneous spatial distribution of velocity profiles across cities, coupled with the fact that faster routes are in general longer than shortest routes.

The collective angular and radial dependence of $\langle I \rangle$ are shown as density plots for the shortest and fastest routes in Figs 3B&C. The monotonic increase of $\langle I \rangle$ with r is apparent in both cases particularly at $r \sim 15\text{km}$ (also shown explicitly in Fig. S4A). The differences in angular dependence can be clearly seen with the fastest routes having a sharp $\langle I \rangle$ at a lower angular range than shortest paths. We note, the absence of any outward bias (negative values of $\langle I \rangle$) at any radial or angular range.

Dimensionless Inness \hat{I} The observed trends for the inness do not take into account the effects of varying travel areas at different distances from the center, or indeed the variation in urban size across the studied cities. To account for these effects we note that the travel area (averaged across cities) increases roughly quadratically with the geodesic distance s (Fig. S4K). Such trend is also observed in [23] when measuring the characteristic shapes of city routes which had travel areas of $O(s^2)$. Therefore, we define a dimensionless, normalized inness thus,

$$\hat{I} = \frac{I}{s^2}, \quad (3)$$

that removes any bias attributed to variations in travel area within and across cities. In Figs. 3D&E, we plot $\langle \hat{I} \rangle$ for the shortest and fastest routes finding that the inness effect is robust to potential biases due to length or area of trips. While the qualitative behavior is similar to that seen for $\langle I \rangle$, the inward tendency of routes is present over a *broader* r and θ for both the shortest and fastest routes. For instance, inward biases are apparent at distances of 5km from the city center, an effect suppressed in $\langle I \rangle$ due to the correspondingly smaller travel area. Furthermore, we now find a relatively more homogeneous distribution of \hat{I} with a comparatively weaker dependence on r and θ . The trend for $\langle \hat{I} \rangle$ continues to point towards the existence of a core-periphery structure in the cities we study (on average), in combination with a smoothly decreasing density distribution of streets away from the center. The weaker angular dependence in particular hints at an isotropic variation in density of

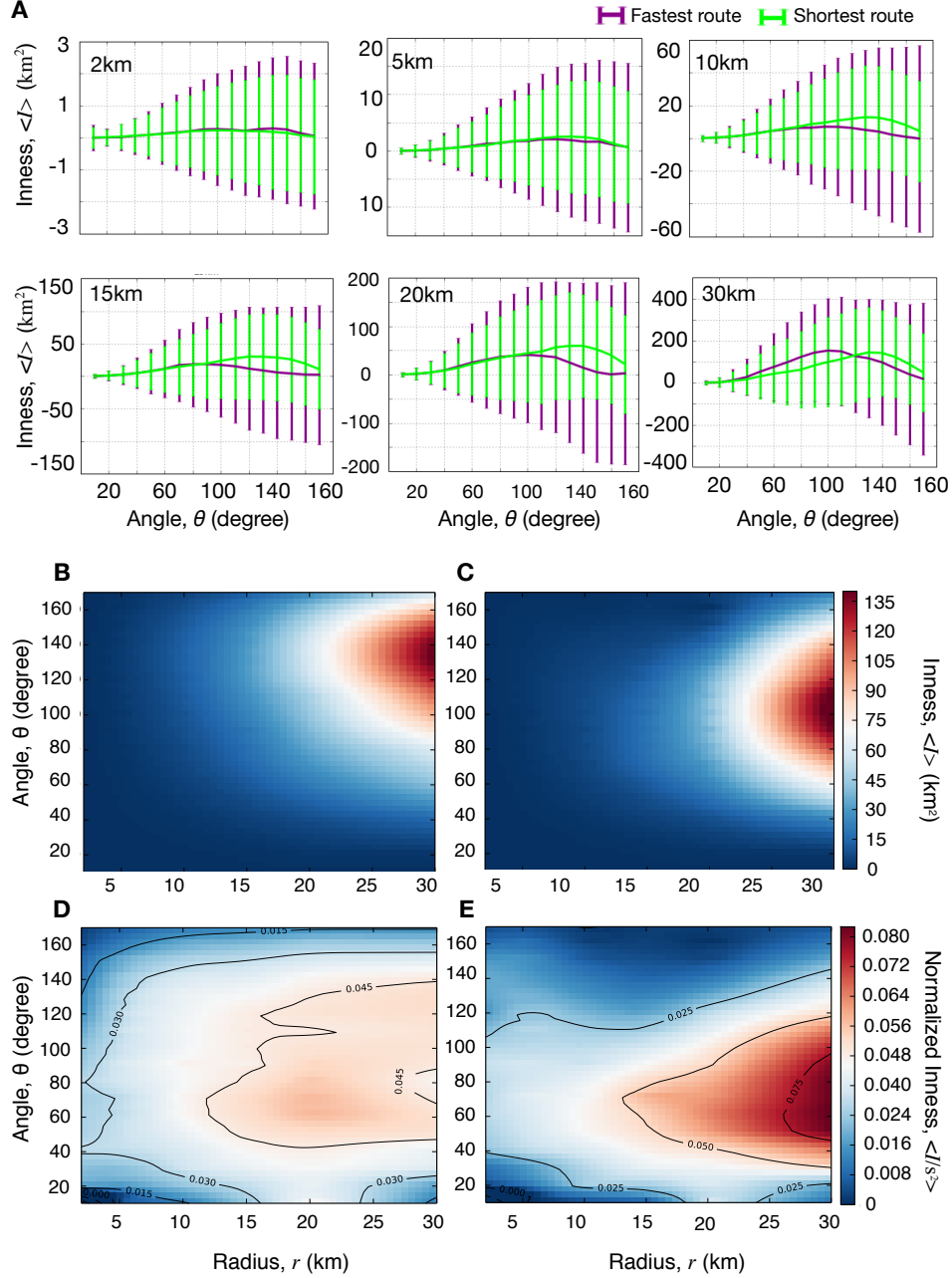


FIG. 3. **The average inness across 92 cities:** **A** The average and standard deviation of I as a function of θ shown for multiple radii r measured from the city center. The curve for the shortest route is shown in green and the fastest route in purple. The density plot of $\langle I \rangle$ in function of r and θ for the shortest routes **B** and fastest routes **C**. The normalized or dimensionless inness $\langle \hat{I} \rangle = \langle I/s^2 \rangle$ for the shortest **D** and fastest routes **E**.

street junctions, suggesting that the majority of cities in our data are *monocentric* as one

would expect to see a neutral inness profile for *polycentric* cities.

The distribution of $\langle \hat{I} \rangle$ is comparatively less homogeneous for fastest routes, primarily due to the presence of link weights (speed limits associated with route segments) adding more variation to the inness profile. Across a wide range of r and θ , $\langle \hat{I} \rangle$ is generally lower than seen in the shortest routes, while there is sharp increase at $15 \leq r \leq 30$ and $40 \leq \theta \leq 100$. This is likely due to the presence of *ring roads* or *bypasses* that serve as attractors for traffic in the city periphery. The lower values of $\langle \hat{I} \rangle$ present in a narrow angular range, even at large r , for both route types, suggests that for $\theta \leq 40$ there is direct connectivity between OD pairs, negating the need to take a detour through routes with higher velocities. This suggests the presence of *sub-cores* near a city’s periphery—*islands of connectivity* separated by relatively limited connectivity *between* the sub-cores.

Inness distribution for individual cities Having examined the properties of average directional biases across urban areas, we now turn our attention to the patterns in individual cities. Indeed, as the fluctuations in Fig. 3A show, there is variability in the inness pattern both within and across cities. In Fig. 4A, each city is plotted as a function of the standard deviation and the average of \hat{I} for the shortest paths, and colored according to its size [36]. A cluster of cities appear in the range $0.01 \leq \hat{I} \leq 0.08$ with some outliers at both positive and negative values of \hat{I} . Ignoring the outliers for the moment, and focusing on the cluster, roughly speaking, we find 3 patterns: **(a)** mildly positive inness in a wide spatial range (cities within the box marked B in the figure); **(b)** a mix of strong positive inness and strong negative inness (points within the box marked C in the figure); and **(c)** a strong positive inness at large distances from the city center (points within the box marked D in the figure). (See SI Figs. S5&S6 for details on individual cities.)

Cities in the first category tend to be large urban areas as shown in Fig. 4B. As a representative case, the density plot of \hat{I} for Berlin (the analog of Fig. 3D) is shown as inset. Cities in the second category are shown in Fig. 4C, with the distribution for Mumbai as an example (there appears to be no correlation with city size). Finally, Fig. 4D shows cities that fall into the third category with Kolkata’s distribution of \hat{I} as inset; these tend to be relatively smaller urban areas. To translate these characteristics into a urban morphology, for a representative city from each category, we plot the spatial distribution of \hat{I} on its geographic map (panels on the right hand column of Fig. 4). The spatial distribution

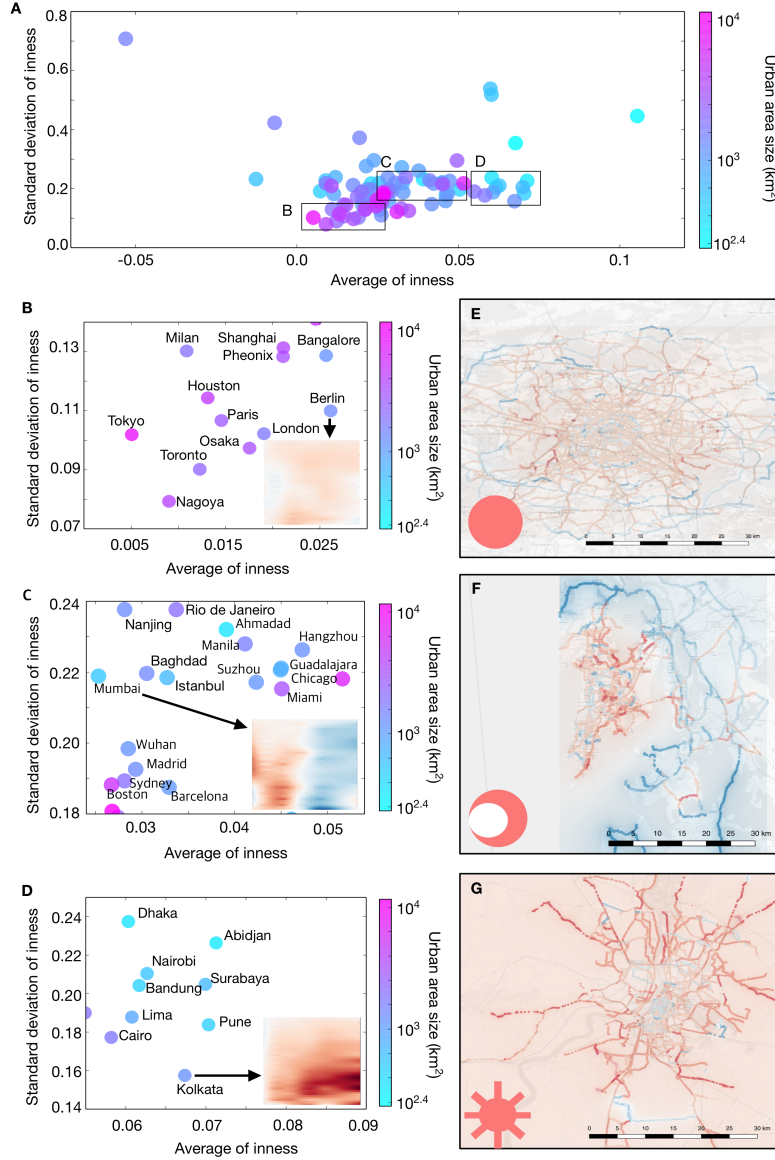


FIG. 4. The average and spatial distribution of the shortest path inness for individual cities **A** The standard deviation plotted in function of average inness for each city. The color of points indicate the urban area size (cf. Ref. [36]). In the same figure, we enlarge three regions marked B, C and D and label the cities explicitly in panels **B,C,D** as well as display in inset the normalized inness density \hat{I} , for representative cities in each region (Berlin, Mumbai, Kolkata). The range of values spans from -0.3 (blue) to 0.3 (red). In **E,F** and **G** we plot the spatial distribution of inness projected on to the physical maps for the three representative cities. The color of street intersections correspond to the average \hat{I} of all routes passing through the intersection. The cartoons in the inset show simplified motifs of spatial layout.

is generated by considering every intermediate point in a city route, and calculating the average \hat{I} of all routes that pass through this particular location. For the considered cities, the values lie in the interval $-0.3 \leq \hat{I} \leq 0.3$ represented as a color spectrum that ranges from blue to red with increasing \hat{I} .

In Fig 4E, we show the spatial distribution of \hat{I} for Berlin, a representative city from the first category. Throughout a wide swathe of Berlin, we find a homogeneous distribution of moderately positive (almost neutral) inness (red), with roads near the city boundary showing a marginally negative inness value (blue). Similar patterns are observed in other large urban agglomerations such as Tokyo and Paris (See SI Figs. S7A&C). These cities tend to have relatively advanced infrastructure and strong levels of connectivity due to the high density of streets, with the homogeneous inward bias suggesting persistent connectivity within 30km of the center. We note that these cities may be mono-centric *or* poly-centric yet have a similar inness profile. Apart from the uniform density of streets this also may be due to the existence of *multiple attracting centers* leading to a neutral inness after averaging. Thus, in terms of directional bias of routes, mono-centric cities with a high connectivity density, or poly-centric cities with multiple socioeconomic centers may be indistinguishable.

Next, we focus on the second category of cities, those with a mix of strong inward *and* outward bias in the route patterns. In Fig 4F, we show the spatial profile for Mumbai which shows two distinct regions with inner and outer bias. The two regions are separated by the Arabian Sea, and connected by (a few) bridges. The left hand side of the map corresponds to the more densely connected part of Mumbai (its economic center) thus most routes within this region have an inward bias. The appearance of the outward bias in the other region is due to the lack of direct connectivity with the economic center, as routes have to pass through one of few bridges that connect the island to the mainland and are thus subject to considerable detour. A similar pattern is seen in other cities in this category, almost all of which have geographic barriers (rivers, seas, hills, mountains) that either spread out across the city, or divide the city into distinct regions. Interestingly, there exist a few cities that have no geographical barrier, but *artificial* barriers attributing a similar effect on route profiles. A notable example of this is Miami which has a prominent rock-mining industrial site in the Western Miami-Dade County (See Figs. S7E&G for this and other examples).

Finally, we examine the spatial distribution of \hat{I} for Kolkata as a city in the third category, shown in Fig 4G. It is apparent that the profile is more distinct than that seen for

Berlin. There appears to be a *hub and spoke* type pattern with the spokes showing high levels of inness, presumably due to its function connecting outer regions to the city center. Correspondingly, as one moves away from the center, there is limited connectivity across the periphery. A similar pattern is seen for other cities in this class (Cairo, Medan, see Figs. S7I&K). There are two possible causes for this: either these cities have a relatively smaller *effective* urban area (regions of strong connectivity), or they are large urban agglomerations with limited or underdeveloped infrastructure. Taken together, the qualitative trends suggest that the cities with a similar spatial inness pattern share streets that have similar connectivity pattern. (See SI Sec.S2 and Fig.S8 for a discussion of the outlier cities).

Differences between shortest and fastest routes in cities The observed difference in the inness patterns of shortest and fastest routes is likely due to the latter being effected by heterogeneous distribution of velocities, in addition to city topology. Additionally, unlike shortest routes, $\langle \hat{I} \rangle$ for the fastest routes display negative values in certain regions (outward bias) as seen in Fig. S6. To further quantify this difference, we measure the Pearson correlation coefficient r of \hat{I} , for each city, shown in Fig. 5E in increasing order from negative to positive values.

To understand this trend, we pick a representative city from each end of the spectrum: Berlin with $r < 0$ and Mumbai with $r \approx 1$. Figs. 5A&B show the spatial distribution of \hat{I} in Berlin for the shortest and fastest routes. Unlike the neutral inness seen for shortest routes, fastest routes display a strong outward bias starting from a radial distance of 15km, which seems to be a consequence of ring-like arterial roads dispersing traffic away from the center. Indeed, this supports our metaphor of competing forces sketched in Fig. 2; the high connectivity of streets in the center of Berlin tends to draw flow towards the city (witnessed by the mildly positive inness profile of the shortest routes) while the faster roads pushes routes outwards. A similar trend is seen for all cities with a negative correlation, with the presence of arterial ring roads (built presumably to alleviate congestion) near the city periphery being the main driver of the differences. Most of these cities, which we term Type I, correspond to the those seen in Fig. 4B, and are large metropolitan areas with mature infrastructure.

Unlike Berlin, Mumbai exhibits virtually identical profiles of inness between shortest and fastest routes, as seen in Figs. 5C&D, with fewer arterial roads or bypasses that can divert

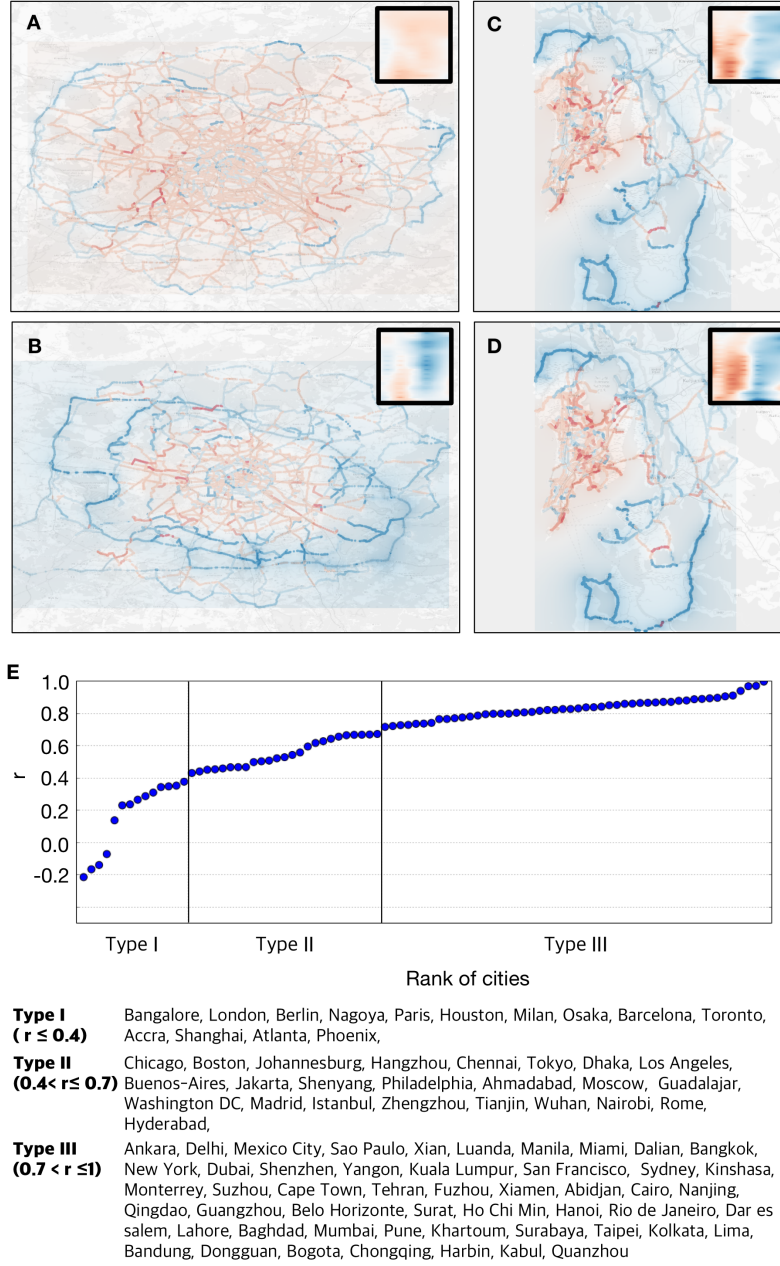


FIG. 5. **Difference between shortest routes and fastest routes** Shortest routes **A** and fastest routes **B** for Berlin. Shortest routes **C** and fastest routes **D** for Mumbai. The insets show the density plots of \hat{I} with the same range as in Fig. 4. **E** Pearson correlation coefficient r between the inness patterns of shortest and fastest routes for each city. Cities are categorized into three groups based on their level of correlation.

traffic away from the city center. In the case of Mumbai, this is due to salient geographic constraints, but a similar pattern is also seen in other cities like Kolkata, that also lack peripheral roads. Thus, cities that either suffer from some kind of geographic constraint, or relatively underdeveloped infrastructure tend to show a higher correlation between the two types of routes. We term these cities Type III, which include the majority of cities in Fig. 4D, along with a few from Fig. 4C.

Cities with intermediate correlation tend to be those with a profile seen in Fig. 4C, and we term these Type II. The behavior seen here seems to be some combination of what drives the trends seen in Type I and Type III cities, and it is difficult to say much more about them at this juncture. As it happens, however, there is the exceptional case of New York. The city shares the same features as Type I cities, *i.e.* it is a large urban area, with highly developed infrastructure, yet, there appears to be a strong correlation between the fastest and shortest routes (Fig. S9). This is likely due to the unique geography of motorways in the New York metropolitan urban area, which unlike typical Type I cities, does not have ring-like motorways in the periphery. Instead New York consists of a series of radial and grid-like motorways whose overall effect is to cancel any observable directional bias.

Discussion

Networks of streets and roads are the primary facilitators of movement in urban systems, allowing residents to navigate the different functional components of a city. Since navigability is a key ingredient of socioeconomic activity, street networks represent one of the key (if not the most important) infrastructural components. Clearly a multitude of factors go into the physical layout of streets, including geographic constraints, design choices, and land parceling among many others. To disentangle these factors, a significant amount of effort has been devoted to understanding the layout of streets across cities globally [5–13, 15–21]. Yet most studies have focused at the microscopic, or local level, primarily through statistics on segments of street networks such as the degree distribution of junctions, shapes of local cells, structural anisotropies and other associated measures.

More than the physical layout, it is the *sampling* of street networks that serves as a true fingerprint of the complex interactions between people, and the flow of goods and services in urban systems. However, there is limited understanding of this facet as existing macroscopic or microscopic measures are not able to fully capture its properties and associated effects.

To fill this gap, we conducted a systematic mesoscale study of street morphology through the introduction of a novel metric that we term inness. The inness encapsulates the direction, orientation and length of routes, thus revealing the morphology of connectivity in street networks, including the distribution of implicit socioeconomic forces that may inform routing choices.

The average inness pattern points towards the existence of a core-periphery structure across the majority of cities with a high density of streets in the city center with a progressively lower density as one moves towards the periphery. This pattern is particularly seen among Type III cities (Figs. 4D, S7I–L) which also happen to be the most numerous in our sample, and therefore dominate the average statistics. This is further confirmed when one looks at the spatial distribution, which reveals a hub-spoke like structure with Kolkata being an archetype. Furthermore these cities tend to have a strong correlation between the sampling patterns of the fastest and shortest routes (Fig. 5E), essentially confirming that the fastest routes also happen to be the shortest routes. Given that many (but not all) cities in this category are in developing countries, this feature seems to indicate a relatively underdeveloped infrastructure with the absence of bypasses, highways, or ring-roads that disperses traffic more efficiently.

Interestingly these qualitative features are somewhat in line with the classical hypothesis of Central Place Theory advanced by Christaller [37]. The theory postulates that cities are organized into hierarchical cores that perform specific economic functions depending on their position in the hierarchy [38]. As the core at the highest level of the hierarchy (which is usually located near the city center) has the most diverse and complex economic functions, lower cores that perform less complex functions need to connect to the higher core to meet the demand of some of the activities in the higher core. Furthermore cores at the lower levels of the hierarchy have minimal interactions between them.

An alternative version advanced by Lösch [39] claims instead that cores at the same level develop specialized and symbiotic functions and thus develop interactions with each other, having the effect of dispersing activity from the center. Indeed, this feature seems to be present in our Type I cities (Figs. 4B, S7A–D), that are predominantly large, and mature urban areas. Cities such as Berlin, Paris, and London, display a relatively neutral inness trend across locations, pointing towards a uniform density of streets across the city. In particular, a comparison of the spatial distribution of inness for the fastest and shortest routes

reveals the presence of ring roads connecting the peripheral areas of the city, and dispersing traffic away from the city center (Fig. 5E). This is further reflected in the low correlation between the morphology of shortest and fastest routes, indicating good connectivity between multiple regions of the city through well established road systems. Considering one of the purposes of building peripheral roads is facilitating material movement around the city, the observed discrepancy between the shortest and fastest routes might reveal that a big, mature urban area starts to decouple the material (resource) movement from human movement via the introduction of ring-roads. This is in line with the assertion that cities tend to transform their social and economic functionality into dematerialized operations as they mature [40–42]

Yet, there are a number of cities that fall between the spectrum of these two levels of categorization. These are predominantly Type II cities that tend to have large fluctuations in their inness value (Figs. 4C, S7E–H), indicating a mix of both inner and outer biases in route choices. Most (but not all) have geographical or artificial constraints within the city (Mumbai, Rio de Janeiro etc.), leading to a mixture of dense and poor connectivity between different locations. Indeed, some have advanced infrastructure (Miami), while others are at a relatively less mature stage (Medan) and they also differ in terms of the size of the urban areas. In fact, as shown in Fig. S10 while there is a monotonically decreasing trend between the Pearson correlation coefficient r and urban area, there is some variability in the inness for those cities that are of intermediate size (some are uniformly well connected, while others have a hub-spoke structure) indicating that evolution process of cities do not necessarily follow a standardized form, being influenced by factors such as geographical features and land-use.

One of the criticisms of Central Place Theory is that it assumes that functional units of the city are static, and correspondingly their place in the hierarchy is fixed. A better reflection of city organization must then take into account the fact that they are constantly evolving through spatial and functional expansion. Our morphological analysis of cities provides evidence of this evolution through the observation that some categories of cities fall into Christaller’s characterization, whereas others into Lösch’s, and which category they fall into depends on their developmental process. Furthermore a proxy for their developmental process is provided by the implicit distribution of socioeconomic forces that generate the inness pattern.

The implications of our result stretch beyond merely movement and its connection with transportation infrastructure, as mobility patterns are also intimately related with the spatial hierarchical distribution of economic activities [43]. While the self-similarity and hierarchy between industries in a city has been studied in detail [40], the connection between the flow of people and goods to its economic hierarchy is less understood. We believe that our present results, with further comparative analysis of street networks and distribution of economic activities will lead to a more comprehensive understanding of urban structures and their evolution.

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- [1] Bettencourt, L. & West, G. A unified theory of urban living. *Nature* **467**, 912–3 (2010).
 - [2] Pan, W., Ghoshal, G., Krumme, C., Cebrian, M. & Pentland, A. Urban characteristics attributable to density-driven tie formation. *Nature Communications* **4**, 1–7 (2013).
 - [3] Batty, M. Building a science of cities. *Cities* **29**, S9–S16 (2012).
 - [4] Sim, A., Yaliraki, S. N., Barahona, M. & Stumpf, M. P. H. Great cities look small. *Journal of The Royal Society Interface* **12**, 109 (2015).
 - [5] Youn, H., Gastner, M. T. & Jeong, H. Price of anarchy in transportation networks: Efficiency and optimality control. *Physical review letters* **101**, 128701 (2008).
 - [6] Cardillo, A., Scellato, S., Latora, V. & Porta, S. Structural properties of planar graphs of urban street patterns. *Physical Review E* **73**, 066107–8 (2006).
 - [7] Justen, A., Martínez, F. J. & Cortés, C. E. The use of space-time constraints for the selection of discretionary activity locations. *Journal of Transport Geography* **33**, 146–152 (2013).
 - [8] Witlox, F. Evaluating the reliability of reported distance data in urban travel behaviour analysis. *Journal of Transport Geography* **15**, 172–183 (2007).
 - [9] da F. Costa, L., Travençolo, B. A. N., Viana, M. P. & Strano, E. On the efficiency of transportation systems in large cities. *EPL (Europhysics Letters)* **91**, 18003 (2010).
 - [10] Wang, P., Hunter, T., Bayen, A. M., Schechtner, K. & González, M. C. Understanding Road Usage Patterns in Urban Areas. *Scientific Reports* **2**, 1001 (2012).
 - [11] Kang, C., Ma, X., Tong, D. & Liu, Y. Intra-urban human mobility patterns: An urban

- morphology perspective. *Physica A* **391**, 1702–1717 (2012).
- [12] Wang, F., Antipova, A. & Porta, S. Street centrality and land use intensity in Baton Rouge, Louisiana. *Journal of Transport Geography* **19**, 285–293 (2011).
 - [13] Rui, Y., Ban, Y., Wang, J. & Haas, J. Exploring the patterns and evolution of self-organized urban street networks through modeling. *The European Physical Journal B* **86**, 74–8 (2013).
 - [14] Louf, R. & Barthlemy, M. A typology of street patterns. *Journal of The Royal Society Interface* **11**, 20140924 (2014).
 - [15] Strano, E. *et al.* Urban Street Networks, a Comparative Analysis of Ten European Cities. *Environment and Planning B: Planning and Design* **40**, 1071–1086 (2013).
 - [16] Masucci, A. P., Smith, D., Crooks, A. & Batty, M. Random planar graphs and the London street network. *The European Physical Journal B* **71**, 259–271 (2009).
 - [17] Jiang, B. A topological pattern of urban street networks: Universality and peculiarity. *Physica A: Statistical Mechanics and its Applications* **384**, 647–655 (2007).
 - [18] Crucitti, P., Latora, V. & Porta, S. Centrality measures in spatial networks of urban streets. *Physical Review E* **73**, 036125–5 (2006).
 - [19] Barthélemy, M. Spatial networks. *Physics Reports* **499**, 1–101 (2011).
 - [20] Batty, M. *Cities and Complexity: Understanding Cities with Cellular Automata, Agent-Based Models, and Fractals* (The MIT Press, 2007).
 - [21] Goh, S., Choi, M. Y., Lee, K. & Kim, K.-m. How complexity emerges in urban systems: Theory of urban morphology. *Physical Review E* **93**, 052309 (2016).
 - [22] Sun, L., Jin, J. G., Axhausen, K. W., Lee, D.-H. & Cebrian, M. Quantifying long-term evolution of intra-urban spatial interactions. *Journal of The Royal Society Interface* **12** (2014).
 - [23] Lima, A., Stanojevic, R., Papagiannaki, D., Rodriguez, P. & González, M. C. Understanding individual routing behaviour. *Journal of The Royal Society Interface* **13**, 20160021–7 (2016).
 - [24] Thomas, T. & Tutert, B. Route choice behavior in a radial structured urban network: Do people choose the orbital or the route through the city center? *Journal of Transport Geography* **48**, 85–95 (2015).
 - [25] De Baets, K. *et al.* Route choice and residential environment: introducing liveability requirements in navigation systems in Flanders. *Journal of Transport Geography* **37**, 19–27 (2014).
 - [26] Viana, M. P., Strano, E., Bordin, P. & Barthélemy, M. The simplicity of planar networks. *Scientific Reports* **3**, 1–6 (2013).

- [27] Barthélemy, M. & Flammini, A. Modeling urban street patterns. *Physical Review Letters* **100**, 138702–4 (2008).
- [28] Clark, C. Urban population densities. *Journal of the Royal Statistical Society. Series A* **114**, 490–496 (1951).
- [29] OpenStreetMap Contributors. Openstreetmap (2015). URL <http://planet.openstreetmap.org>. [Online; accessed 02-February-2016].
- [30] Morris, R. G. & Barthelemy, M. Transport on coupled spatial networks. *Physical Review Letters* **109**, 128703–4 (2012).
- [31] Strano, E., Shai, S., Dobson, S. & Barthélemy, M. Multiplex networks in metropolitan areas: generic features and local effects. *Journal of The Royal Society Interface* **12**, 20150651–9 (2015).
- [32] Ashton, D. J., Jarrett, T. C. & Johnson, N. F. Effect of congestion costs on shortest paths through complex networks. *Physical Review Letters* **94**, 058701–4 (2005).
- [33] Jarrett, T. C., Ashton, D. J., Fricker, M. & Johnson, N. F. Interplay between function and structure in complex networks. *Physical Review E* **74**, 026116–8 (2006).
- [34] latlong.net (2016). URL <http://www.latlong.net/>. [Online; accessed 20-December-2016].
- [35] Lee, S. H., Cucuringu, M. & Porter, M. A. Density-based and transport-based core-periphery structures in networks. *Physical Review E* **89**, 032810–14 (2014).
- [36] Demographia. Demographia world urban areas (built up urban areas or world agglomerations) 11th annual edition (2015). URL <http://www.demographia.com/db-worldua.pdf>. [Online; accessed 24-August-2016].
- [37] Christaller, W. *Central places in southern Germany* (Prentice-Hall, 1966).
- [38] Brian J. L. Berry, W. L. G. The functional bases of the central place hierarchy. *Economic Geography* **34**, 145–154 (1958).
- [39] Losch, A. *et al. Economics of location* (Yale University Press, 1954).
- [40] Youn, H. *et al.* Scaling and universality in urban economic diversification. *Journal of the Royal Society, Interface* **13** (2016).
- [41] Pumain, D., Paulus, F., Vacchiani-Marcuzzo, C. & Lobo, J. An evolutionary theory for interpreting urban scaling laws. *Cybergeo : European Journal of Geography* 1–22 (2006).
- [42] Bettencourt, L. M. A., Samaniego, H. & Youn, H. Professional diversity and the productivity of cities. *Scientific Reports* **4**, 3–8 (2014).

- [43] Batty, M. Hierarchy in cities and city systems. *Hierarchy in Natural and Social Sciences*, 143–168 (Springer, 2006).